# Support Vector Machines: Maximum Margin Classifiers

Nipun Batra

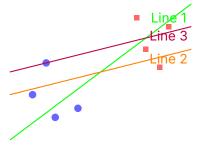
IIT Gandhinagar

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# Outline

# The Problem with Many Decision Boundaries

**Question:** For linearly separable data, which line should we choose?



**All lines separate the data perfectly!** Which is best for new, unseen data?

# Pop Quiz: Decision Boundary Selection

#### **Quick Quiz 1**

Among all possible separating lines, which criterion should we use to choose the best one?

a) The line closest to the data points

**Answer:** b) Maximum margin! The line farthest from both classes generalizes better.

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#### **Quick Quiz 1**

Among all possible separating lines, which criterion should we use to choose the best one?

- a) The line closest to the data points
- b) The line that maximizes distance to closest points
- c) Any line works equally well

**Answer:** b) Maximum margin! The line farthest from both classes generalizes better.

### **SVM Principle**

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### Intuition

**Larger margin** = More confident predictions = Better generalization to new data

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### **Derivation Intuition**

• Find point  $x_1$  on first hyperplane

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- Find point x<sub>1</sub> on first hyperplane
- Move perpendicular distance t in direction w:

$$\mathbf{x}_2 = \mathbf{x}_1 + t \frac{\mathbf{w}}{\|\mathbf{w}\|}$$

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- Substitute into second hyperplane equation
- Solve for t to get distance

# Pop Quiz: Hyperplane Distance

#### **Quick Quiz 2**

What is the distance between hyperplanes 2x+y-3=0 and 2x+y+1=0?

a) 1 unit

**Answer:** c)  $D = \frac{|(-3)-1|}{\sqrt{2^2+1^2}} = \frac{4}{\sqrt{5}}$  units

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Goal: Find hyperplane that maximizes margin

# Hard-Margin SVM Formulation

Minimize: 
$$\frac{1}{2} \|\mathbf{w}\|^2$$
 (1)

Subject to: 
$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \ge 1 \quad \forall i$$
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### Why this formulation?

- Minimizing  $\|\mathbf{w}\|^2 \Rightarrow$  Maximizing margin  $\frac{2}{\|\mathbf{w}\|}$
- Constraint ensures all points are correctly classified
- Support vectors lie exactly on margin boundary:  $y_i(\mathbf{w} \cdot \mathbf{x}_i + \mathbf{b}) = 1$

# Pop Quiz: SVM Constraints

#### **Quick Quiz 3**

In the SVM constraint  $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \ge 1$ , what does  $y_i = +1$  and  $\mathbf{w} \cdot \mathbf{x}_i + b = 0.5$  mean?

a) Point is correctly classified and satisfies constraint

**Answer:** b) Since  $1 \times 0.5 = 0.5 < 1$ , the constraint is violated!

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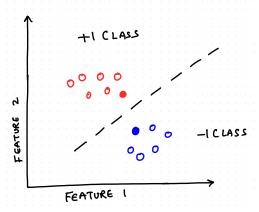
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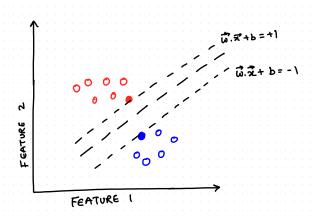
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- b) Point violates the constraint
- c) Point is a support vector

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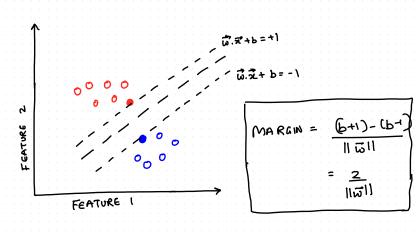




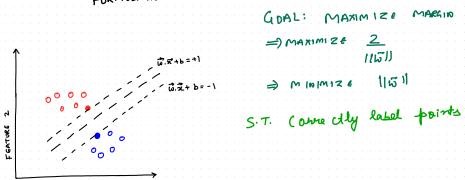




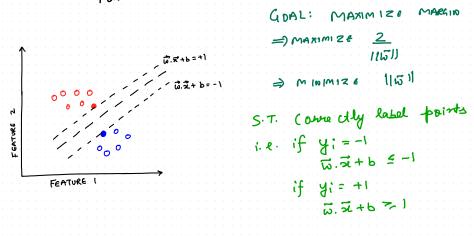
FORMULATION



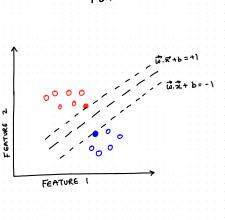




EDRMULATION



### FORMULATION



GDAL: MAXIMIZE MARGIN

=) MAXIMIZE 2

ITWI)

=) [MINIMIZE [[W]]

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e. if  $y_i = -1$ 

y; (2.7+6) 71

Q) What is  $\|\mathbf{w}\|?$ 

### Q) What is $\|\mathbf{w}\|$ ?

$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}$$

$$\|\mathbf{w}\| = \sqrt{\mathbf{w}^{\top}\mathbf{w}}$$

$$= \sqrt{\begin{bmatrix} w_1 & w_2 & \cdots & w_n \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}}$$

EXAMPLE (IN 10)

